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Abstract: Blind hyperspectral unmixing basically consists of three sub problems. First is Subspace identification that is finding the number of pure endmembers present. Second is endmember extraction and third is abundance estimation. There are many approaches for endmember extraction and abundance estimation in literature. But many approaches require prior information for the number of endmembers. In this paper, new approach based on eigenvalues of the hyperspectral image for subspace identification is proposed, which is best suitable for real-time application like wild land fire tracking, biological threat detection and monitoring of oil spills. We have compared our results with other state-of-art algorithms on the real and synthetic dataset which shows the effectiveness of the proposed work.

Keywords: Hyperspectral, Subspace identification, Eigen values, unmixing

1. Introduction

Hyperspectral devices or Imaging spectrometers captures tens to hundreds of narrow spectral bands of the scene from optical wavelength bands approximately at the same time. This technology represents the succeeding era in the spectral dimension of the progress of multispectral imaging sensors. Hyperspectral sensors can be applied to all major areas of earth and planetary science including land use (Kalluri et al., 2010), water characteristics (Mishra et al., 2017) and atmospheric characterization (Elwell et al., 2006) due to high spectral resolution. Land applications include all types of vegetation studies, soil science, geology, and hydrology (Chang, 2003). Hyperspectral sensors can be used in river, ocean, and lake for water quality, biochemical studies, and bathymetry analysis. Various parameter measurement, various analysis and characteristics of the atmosphere can be studied using hyperspectral sensors.

The scene depicted by a single pixel usually covers more than one different endmember or material due to multiple scattering, intimate mixing, and low spatial resolution. The spectral signature of different substances/objects is recorded into one mixed spectral response. The pixels that are composed of more than one spectrally distinct material are called mixed pixels. Depending on the spectral and spatial resolution of the hyperspectral sensor under the study, the mixed pixel may contain either different landuse or land cover types of dissimilar endmembers. Mixing can be linear or non-linear depending on how endmembers are related to each other in a single pixel. Decomposition of the mixed pixel is to extract subpixel level information is called spectral unmixing (Bioucas-Dias et al., 2012), as shown in figure 1. Automatic spectral unmixing chain consists of three stages. First is subspace identification which finds the number of pure spectral signatures present in the image. Second is endmember extraction which is extracting pure spectral signatures from the image itself. The final and third stage is abundance estimation to quantify various materials in a scene. Subspace identification is a very crucial step in unmixing chain as it provides initial information to subsequent stages. Realtime applications of hyperspectral image processing applications require fast approaches. There exist many approaches to hyperspectral subspace identification but all of them requires high processing time which is not suitable for real-time processing.

There are many popular subspace identification methods Principal Component Analysis (PCA), Singular Value Decomposition (SVD), Hyperspectral Subspace Identification by minimum error (Hysime), Harsanyi-Farrand-Chang (HFC). PCA (Jolliffe, 2011) is one of the statistical methods commonly used in signal and image processing for dimensionality reduction and decorrelation. PCA is a factor analysis approach with the consideration of the total variance in the data to convert the original variables into a lesser set of linear mixtures. Subspace for the hyperspectral image is calculated based on variances contained by principal components. SVD (Lange, 2010) finds singular values unlike principal components in PCA. But the method of finding subspace of SVD is same as in PCA. The only main difference is the principal component and singular values. HFC (Chang and Du, 2004) method is eigenvalue thresholding method using Neyman-Pearson detection to resolve subspace identification, which models the dimensionality estimation as a binary composite hypothesis testing problem and the subspace approximation error can be measured by ROC analysis. Hysime (Bioucas-Dias and Nascimento, 2008) uses the least mean squared error-based method to gather the signal subspace in hyperspectral images.

In this paper, we propose a new approach for subspace identification in the hyperspectral unmixing chain. The main advantage of our approach is fewer computations which is best suitable for real-time applications. Contributions from this paper are:

- We have developed new TE (Thresholding Eigenvalues) for subspace identification.
- Timing analysis for the proposed approach and other state-of-art approaches.



Figure 1: Automatic spectral unmixing chain

3.

Results

2. TE (Thresholding Eigenvalues)

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Hyperspectral images are basically 3D-cube. Two dimensions are spatial and one dimension is spectral. To compute the correlation matrix easily, the two-dimensional image is required with one spatial and one spectral dimension. Y is the two-dimensional version of original three-dimensional hyperspectral image X. Y is having a size of $M \times B$, where M is a number of pixels and B is the number of bands.

Correlation is a very basic operation in signal processing community to find similarity between two signals. Here, R is correlation matrix of Y, which represents bands similarity. Eigenvalues are invented with the purpose of finding the principal axes of a rigid body. As Eigenvalue represent principal axes, we can assume eigenvalues as the prime component. Higher eigenvalue means more basic component. If we find few eigenvalues, which represent whole data then that few numbers represent hyperspectral subspace dimension. E is eigenvalue set of correlation matrix R. Es is descending sorting of vector E. Es is calculated to find first major components which have more impact. L is normalized values of Es. Normalization is necessary to deal with a high dynamic range of eigenvalues.

The algorithm requires two variables for computation. One is two-dimensional hyperspectral image and second is the variance that needs to be preserved from eigenvalues. Var is a variable, which represents variance required. (Var/100) gives a value between 0 and 1. Variable Var value should be between 0 and 1 to compare it with normalized value of eigenvalues L. TE approach finds a value of N such that first N eigenvalues from L give variance greater than or equal to (Var/100). N is hyperspectral subspace dimension which represents the number of pure spectral signatures present in the image.

This TE approach requires few computations only to find N. The advantage of fewer computation in TE approach is very useful in real-time hyperspectral unmixing. Figure 2 shows the flowchart of the TE algorithm.

We have performed two types of analysis on both real and synthetic dataset. First is timing analysis and second is subspace analysis (Figure 3).



Figure 2: Flowchart of TE algorithm



Figure 3: Timing Analysis for synthetic images

Cuprite image as shown in figure 4 is used as real dataset which can be downloaded from URL: https://sites.google.com/site/feiyunzhuhomepage/datasets -ground-truths. Cuprite image was taken by AVIRIS instrument which is an optical instrument that delivers images of the spectral radiance from 400 to 2500 nm wavelength range with overall 224 contiguous spectral channels.

We have used synthetic data generated from Hyperspectral Imagery Synthesis (EIAs) toolbox (Computational Intelligence Group, 2019). All these synthetic images are shown in figure 5 have been generated using 5 selected materials (asphalt, brick, fiberglass, Sheetmetal, vinylplastic from the USGS spectral library (Clark et al., 2007).





Figure 5: Synthetic images

Figure 4: Cuprite image

Each image is of 128x128x431. Five synthetic images (Matern, Exponential, Spheric, Rational, and Legendre) as shown in figure 5 are generated using different modelling equations available in the toolbox (Computational Intelligence Group, 2019).

3.1. Timing analysis

Processing time is very important for real-time applications. Some applications of hyperspectral images require less computation time. In this experiment, we have depicted processing time by each algorithm and compared with our approach as shown in figures 3 and 6. Processing



Figure 6: Spectral signatures used in the synthetic image

3.2. Subspace analysis

Subspace is also as important as timing in real time hyperspectral unmixing chain. Subspace provides the number of spectrally distinct signatures. Subspace analysis observes the number of pure signatures for the unsupervised spectral unmixing chain. Figures 7 and 8 show the subspace analysis experiment results for synthetic and real image respectively. As synthetic images are generated using the toolbox, we know the subspace dimensions. For our synthetic dataset, we have used five distinct signatures. So, reference data for all synthetic images is figure 5. We have compared subspace dimensions for our proposed approach and other approaches. All approaches except HFC gives perfect subspace dimensions. Reference data for cuprite image is 14 as mentioned in paper (Zhu et al., 2014).

We have compared subspace dimensions in figure 8 for cuprite image. It can be seen that HFC and our proposed algorithm gives the same result as GT (Figure 9).









Figure 7: Subspace analysis for real image

In this paper, a new Thresholding Eigenvalues based to identify approach is proposed the subspace dimension of the hyperspectral image. The simulation results of the timing analysis and subspace analysis of proposed approach was computed form both synthetic and real dataset. TE approach computes subspace dimensions accurately and comparatively in less time. TE approach can be best suitable for real-time applications.

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